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Identifying Sources of Heterogeneity for Empirically Deriving Strategic Types: A Constrained Finite-Mixture Structural-Equation Methodology

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The resource-based view (RBV) of the firm suggests that strategic deployment of capabilities allows strategic business units (SBUs) to exploit distinctive competencies and create sustainable competitive advantage. Following the RBV, we propose a new predictive methodology for deriving typologies of SBUs that accommodates heterogeneity among SBUs with respect to their strategic capabilities, how effectively they are employed, and performance. Statistically, we devise a constrained finite-mixture structural-equation procedure that simultaneously accounts for firm capabilities, performance outcomes, and the relationships between them. The procedure allows for a comprehensive modeling and grouping of entities, and simultaneously provides a diagnosis of the sources of heterogeneity via the flexibility of estimating a series of nested models. Managerially, our proposed methodology is grounded in the strategic type and RBV literature and can capture the effects of environmental and industry-specific factors. Using data obtained from 216 SBUs in the United States for illustration, the results show that our derived *four mixed-type solution* dominates the four-group, *Prospectors-Analyzers-Defenders-Reactors* classification as well as a number of other nested model solutions in terms of objective statistical fit criteria for this data set, suggesting a more contingency-driven strategic stance adopted by these SBUs. We conclude with a discussion of the theoretical and managerial benefits of an improved methodology for empirically deriving strategic typologies.

Key words: competitive strategy; strategic types; effectiveness performance; structural-equation models; finite mixtures; latent class models
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1. Introduction

According to the resource-based view (RBV) of the firm (Wernerfelt 1984; Barney 1986, 1991; Barney and Zajac 1994), firms or strategic business units (SBUs) deploy their resources and capabilities strategically, allowing them to exploit their distinctive competencies in the best way possible to create sustainable competitive advantage. That is, the capabilities themselves help the SBU perform better, but performance is further improved for SBUs that have the abilities to put these capabilities to best use. The SBUs that best develop and manage their resources and capabilities through time will outperform their competitors (see Hitt and Ireland 1985). Early work by Penrose (1959) that greatly influenced the RBV argued that managers who strategically deploy capabilities, and add capabilities to the existing capability base that best allow the SBU to implement its growth plans, will be rewarded with higher growth rates and performance levels. The RBV defines capabilities as bundles of skills and knowledge that allow SBUs to make best use of the assets they possess and to efficiently coordinate their activities (Day 1990, p. 38). SBU-specific capabilities are deeply rooted in the SBU's routines and practices and therefore are usually difficult for competitors to imitate (Dierckx and Cool 1989). These SBU-specific capabilities are the SBU's main source of long-term competitive advantage and performance, and it is up to SBU management to exploit them to their greatest advantage.

An ideal typology of SBU strategy deployment should be able to account for heterogeneity among SBUs with respect to their capabilities, how effectively they are exploited, and the resulting performance. The most popular typology in the management literature of strategic capabilities is that of Miles and Snow (1978), hereafter denoted as M&S. The M&S typology has been widely applied in both the management and marketing strategy literatures since its initial inception in the late 1970s (see e.g., Hambrick 1983, Conant et al. 1990, Walker et al. 2003) and is still viewed as a landmark conceptual model well over 25 years later (Hambrick 2003). This generic typology subjectively classifies businesses based on their patterns of strategic decisions into four categories: *Prospectors*, *Analyzers*, *Defenders*, and *Reactors* (P-A-D-R) (to be elaborated below).

The original M&S model has been refined in subsequent research studies in several ways. Although the authors found clear relationships between strategic types and capabilities, M&S did not fully explore the performance consequences of strategic deployment of capabilities, other than to note that the three "archetypal" strategic types (*Prospectors*, *Analyzers, and Defenders*) all outperform the *Reactors*. They did not determine empirically whether, for example, some *Prospectors* might outperform *Defenders* or other *Prospectors*. As Hambrick (1983, p. 7) noted:

> The typology ... has limitations. Its parsimony can be taken as an incomplete view of strategy. Its generic character ignores industry and environmental peculiarities. In fact, Miles and Snow (1978) ... stressed that the various strategic types would perform equally well in any industry, providing that the strategy was well implemented. This latter stance is inconsistent with the more typical view that an environment favors certain types of strategies ... . The typology appears to warrant more development and testing. As noted, little consideration of the environment-strategy link has been given. No systematic evidence has been provided on how strategic types differ in their functional attributes ... .

Hambrick (1983) attempted to relate differences in performance to differences in strategy conditioning on environmental and functional attributes. Many of his findings conflict with those predicted from M&S, and suggest that deeper empirical research into the relationships between capabilities, strategic type, and performance across a wider range of industries is warranted. In a later study, Hambrick (1984) criticized the M&S typology for its lack of rigor and limited predictive power, as it is conceptually based and not quantitatively derived (Hambrick 1984, p. 28):

> Even though they are based on systematic empirical observation, they are not quantitatively based. Typologies represent a theorist's attempt to make sense out of non-quantified observations. They may have the advantage of being "poetic" ... that is ring true, often sounding very plausible. However ... they may serve well for descriptive purposes but have limited explanatory or predictive power ... .

Conant et al. (1990) expanded on the M&S typology to explicitly examine the relationships between capabilities and performance. Although they did not study any capabilities other than marketing-related ones, their findings did suggest that the interrelationships between strategy, capabilities, and performance are complex. It may thus be overly simplistic to classify SBUs solely by capabilities, as within any one strategic type, different firms will have different bundles of capabilities and/or will deploy them differently, leading to a range of performance outcomes. For this reason, a typology built simply on strategic capabilities may adequately describe a set of industries, but will obscure intratype differences in capabilities and performances, and hence be inadequate in explaining performance outcomes or making recommendations to firms. The Conant et al. view, then, is consistent with RBV theory that suggests that the mere presence of a capability is no guarantee that it will be exploited effectively or that performance will be positively affected.

The evolution of the M&S criticisms as outlined above (consideration of profit consequences, quantitative rigor, and explicit inclusion of the relationship between capabilities and performance) provides some guidance as to what an ideal strategic typology might resemble, especially given the RBV. In this paper, we develop a quantitative methodology for empirically deriving strategic typologies that model SBU heterogeneity in terms of strategic capabilities, performance outcomes, and the relationships between them. Rather than using only strategic capabilities as the sole basis for *subjectively* forming strategic types as in M&S, our methodology is quantitative (consistent with Hambrick 1983, 1984) and empirically derives strategic types based on heterogeneity in levels of performance, levels of strategic capabilities, and/or the strengths of relationships between capabilities and their performance outcomes.

We construct a flexible finite-mixture structural-equation methodology which, through a series of nested model specifications and statistical test heuristics, can identify the most significant sources of heterogeneity, and therefore the most appropriate basis for formulating strategic types. We account for three major potential sources of heterogeneity across strategic types: heterogeneity with respect to (a) strategic capabilities, (b) performance, and (c) the relationship between strategic capabilities and performance. Our approach is data driven: it explores the structure in the data to simultaneously uncover what the nature and composition of the strategic types should be. In addition, it can be shown to accommodate the approaches of M&S, Conant et al. (1990), and others as special cases via nested or constrained models/solutions.

We gather data on 216 SBUs/divisions located in the United States, representing a diverse set of industries, to illustrate and compare our approach to that of M&S. We find that our derived four "mixed-type" solution empirically dominates the four-group P-A-D-R classification (as well as a number of other nested model classifications) in terms of objective statistical criteria. In addition to differences in capabilities, we uncover differences in the performance levels and in the relationship between strategic capabilities and performance, both of which would have been missed if only the M&S typology had been applied to this sample.

This paper extends the research presented in DeSarbo et al. (2005) in several ways. In their recent article, DeSarbo et al. (2005) re-examined the M&S strategic typology by focusing on capabilities, environmental uncertainty, and performance. They applied a constrained, multiobjective classification methodology (NORMCLUS) to derive empirical strategic types which were characterized by different environmental circumstances, distinct capabilities, different strategic choices, and ultimately different performance levels. The objective of their study was to maximize associations and interrelationships, not causalities, between these batteries of variables (environment, capability, strategy, and performance). They found that the new empirically-derived typology was more closely aligned to these environmental circumstances, strategic capabilities, and performance variables than the "pure" M&S strategic typology with respect to an international sample of firms from Japan, China, and the United States.

The objective of this paper is to derive a *predictive* methodology to uncover empirically-driven strategic typologies that can provide managerial as well as theoretical benefits. This study differs from that of DeSarbo et al. (2005) in several ways. First, we devise a constrained finite-mixture structural-equation-based methodology to derive strategic typologies that formally model the interrelationships between capabilities and performance. This methodology permits predictive modeling as opposed to the descriptive, data analytic classification methodology of DeSarbo et al. (2005). Second, our proposed methodology also differs from DeSarbo et al. (2005) as it provides a diagnosis of the sources of heterogeneity via the flexibility of estimating a series of nested models. In the structural equations provided, we use performance measures (profit and return on investment (ROI)) as outcome variables, and thus can examine the impacts of the various capabilities on performance, and how these impacts differ for different strategic types. This simply cannot be done in DeSarbo et al. (2005). Third, the methodology devised in this manuscript is grounded in the RBV of the firm, which suggests that managerial investment in, and deployment of, key capabilities will significantly impact SBU performance. There is no theoretical analogue underlying the data analytic exercise in DeSarbo et al. (2005).

Our managerial contribution is as follows. The original M&S typology has been criticized for not providing deep managerial insights with respect to decision making, except to note that it is preferable to pursue a *Prospector, Defender*, or *Analyzer* strategy. We find that for different strategic types, different capabilities are related to better performance measures. This finding is consistent with the expectations of the RBV. Therefore, a contingency approach is recommended: given the adopted strategic posture, the practicing manager can determine whether the SBU has the proper mix of capabilities. Management can make better decisions on allocating scarce resources to strengthen or better deploy the capabilities most critical for improved performance, given the SBU's strategic objectives.

Section 2 presents the theoretical background. Section 3 describes our research methodology. Section 4 discusses the constrained finite-mixture structural-equation model that we employ to derive the strategic typologies. Section 5 reports the results of our empirical application, and §6 discusses the respective managerial implications and summarizes the overall methodological and substantive contribution of this manuscript.

2. Theoretical Background

2.1. SBU Strategic Capabilities

According to the RBV, capabilities are "complex bundles of skills and accumulated knowledge that enable SBUs to coordinate activities and make use of their assets" (Day 1990, p. 38), and to create economic value and sustain competitive advantage. While the list of capabilities an SBU may have is enormous, in this study we focus our efforts on five categories of capabilities which are closely linked to sustainable competitive advantage and long-term success (Day 1994, Conant et al. 1990, Jaworski and Kohli 1993). These include technology, market linking, marketing, information technology (IT), and management capabilities. Technical capabilities allow the SBU to improve production process efficiencies, reduce costs, and increase competitiveness. Market linking capabilities such as market sensing and distribution channel linking let the SBU exploit marketplace opportunities. Capabilities in marketing, management, and IT are also related to increased performance (e.g., profitability), and the SBU's ability to sustain competitive advantage (Conant et al. 1990, Jaworski and Kohli 1993, Day 1994).

2.2. Strategic Types and SBU Strategic Capabilities

Based on exploratory field studies conducted in textbook publishing, electronics, food processing, and health care, M&S developed a strategic typology (*Prospectors, Analyzers, Defenders,* and *Reactors*) classifying organizations according to enduring patterns in their strategic behavior. M&S found relationships between strategic types and SBU capabilities. *Prospectors* use their product engineering and R&D skills to compete, *Defenders* seek to maintain a protected niche in a stable product area, and *Analyzers* occupy a middle ground, exhibiting characteristics of both *Prospectors* and *Defenders*. These three "archetypal" strategic types perform well, as long as the strategies are implemented effectively. A fourth type, *Reactors,* do not show consistency in their strategic decisions and are outperformed by the other three types. Because *Prospectors* compete by using a first-to-market strategy, anticipating new product and market opportunities through technological innovation, technological capabilities would be particularly important for them to succeed (Walker et al. 2003). Solid ties with the distribution channel and good market research are also important for *Prospectors* to ensure their research and development (R&D) results in products that meet customer needs (Hambrick 1983, McDaniel and Kolari 1987, Shortell and Zajac 1990). In addition, IT capabilities allow for better cross-functional integration critical to new product development (Griffin and Hauser 1996, Bharadwaj et al. 1999). By contrast, *Defenders* need to be able to offer higher quality and service and/or lower prices to succeed, and concentrate on resource efficiency, cost cutting, and process improvements. For them, marketing and market linking capabilities may be most critical for their continued success (Conant et al. 1990, Walker et al. 2003) because they rely on their more limited range of products or services, and protect their domains by offering superior quality and service, and lower prices.

The objective of M&S was to find evidence of strategic types within the industries they studied. While they made some *observations* regarding SBU capabilities and other business attributes, environmental factors, and performance (i.e., *Reactors* are outperformed by the other three types), it was not their goal to quantify empirically the relationships among these factors. According to M&S, successful prospecting should strengthen technology and IT capabilities, and successful defending should strengthen market linking and marketing capabilities. As Hambrick (1983) stated, "*Prospectors* tend to want to continue prospecting." Likewise, *Defenders* will want to continue defending, and *Analyzers* will want to build up capabilities appropriate to both prospecting and defending. Thus, M&S suggest (although never empirically tested) that within each strategic type, certain capabilities will be particularly important to sustained performance, and that those SBUs that are able to fully use these capabilities will perform better.

A typology built solely on capabilities may fail to identify performance differences within the derived strategic types, and will be of limited use as a predictive or explanatory model. Using the relationships between capabilities and performance to derive the typology will result in groups of SBUs that are similar in the ways they use their capabilities to succeed. For example, some *Prospectors* may exploit new markets using superior technology capabilities, some may exploit new markets using strengths in IT or management capabilities, and the first group may outperform the second group. Such intratype differences would have been obscured had the relationships between capabilities and performance not been considered, as would the managerial implications of such a finding. The evolution of the M&S typology presented in the introduction depicts the various improvements required as suggested by subsequent authors (e.g., Hambrick 1983, 1984; Conant et al. 1990) to account empirically for the effect of capabilities on performance, thus making the model more useful in a predictive or explanatory way.

To develop our methodology for strategic typology identification, we apply principles of the RBV which has proven to be a very useful framework in strategy analysis. Unlike the industrial-organization (IO) model, in which SBUs within an industry have comparable strategic resources and external forces have the greatest impact on SBU performance, the RBV proposes that differences in managerial actions account for different performance levels among comparable SBUs (Amit and Schoemaker 1993, Day and Wensley 1988, Peteraf 1993). That is, management at the best-performing SBUs organizes, deploys, and protects the firm's existing base of capabilities most effectively (Penrose 1959), and also strategically adds capabilities that best complement the existing capability base (Hitt and Ireland 1985) to create sustainable competitive advantage and extract economic rent. Because sustainable competitive advantage is not easily imitated or substituted, the SBU that cultivates it most successfully will outperform its competitors (Hunt and Morgan 1995).

Under the RBV, it would be expected, as Hambrick (1983) noted, that *Prospectors* would want to keep on prospecting, and *Defenders* would want to keep on defending to improve performance. That is, SBU performance is not driven by external forces as in the IO model. Performance is actually driven by the interrelationship between the SBU's existing capabilities and the prevailing environmental factors. Managers can influence the level of performance they attain by correctly choosing capabilities that add the most to their core competencies, given their limited financial resources. Under this view, SBUs would seek to build capabilities that added to their respective core competencies, allowing them to maintain their sustainable competitive advantage and to improve their performance (hence, *Prospectors* would keep on prospecting). The managers who consistently support, and add to, the capabilities most important to performance within their SBU's industry will be rewarded with the highest performance levels. This effect would account for two comparable *Prospectors*, for example, to have quite different performance levels through time.

Consistent with the literature on strategic types and the RBV, our goal is to empirically derive strategic types from observed data, simultaneously considering SBU capabilities, profitability, and their potential interrelationships. Model selection heuristics are developed to identify the appropriate number of strategic types. The model's statistical framework accommodates various constraints regarding the positivity of the estimated coefficients, as well as various equality restrictions to accommodate special nested models (e.g., the M&S typology). Posterior probabilities of SBU membership in each derived strategic type are simultaneously estimated as well. Thus, we wish to provide a quantitative approach to the derivation of strategic types which optimizes an objective likelihood function, is based on key factors such as strategy, performance, and their potential relationships, and can provide insight as to the nature and number of these derived strategic types and their SBU composition. As will be shown, the quantitative framework provides a manner in which to compare the derived strategic types with any rival typology (including that of M&S) on objective statistical criteria related to explanatory power and prediction. In addition, a number of nested models are specified to examine the structure in the data and identify the various sources of heterogeneity that determine the derived strategic types. We now describe our research methodology.

3. Methodology

3.1. Development of Firm Capability Scales

We followed the multistep instrument development approach suggested by Churchill (1979) to develop and validate scales for the capabilities included in our study. In the first step, we identified relevant measurement scales from the marketing literature and grouped the scale items derived from these scales into the capability types. To this initial pool, we added new items in instances where it was felt that not all the dimensions of the construct had been sufficiently covered. The scales were refined through in-depth focus interviews with managers in two SBUs. According to these interviews, the managers perceived the scale items to be relevant and complete, and were able to rate their own SBU relative to major competitors easily on each scale item.

In the second step, we assessed construct validity of the scales being developed by correcting ambiguous scale items or those that have possessed "different shades of meaning" to informants. We established convergent and discriminant validity using Davis's (1989) procedure. A team of seven judges with background in measurement development was asked to sort the items from the first step into the five strategic capability scales, and interrater reliability was assessed.

In the third step, we reexamined all scale items and eliminated inappropriate or ambiguous items or any that were inconsistently classified. The scales were then combined into an overall instrument for additional pre-testing. The instrument was distributed to 32 managers in the two SBUs to further assess scale reliability and validity, and items that remained troublesome were deleted. The instrument was also distributed to 41 Executive Master of Business Administration (EMBA) students taking a new product development class, and the results were factor analyzed. Two additional items that did not load appropriately were deleted. The resulting five strategic capability factors were:

Market Linking Capabilities. These include market sensing and linking outside the organization. The scale items used were derived from Day's (1994) descriptions of market linking capabilities. Using 0 to 10 point scales (0 = much worse than our competitors and 10 = much better than our competitors), respondents rated their SBUs, relative to the top three competitors in their industry on their capabilities in creating and managing durable customer relationships, creating durable relationships with suppliers, retaining customers, and bonding with wholesalers and retailers. The coefficient Cronbach alpha for these items was 0.84, indicating high measurement reliability.

Technology Capabilities. These capabilities relate to process efficiency, cost reduction, consistency in delivery, and competitiveness. The scale items were drawn from Day's (1994) descriptions of technological capabilities. Using the same 0 to 10 point scales, respondents rated their SBUs relative to the three major competitors in their industry on their capabilities in new product development, manufacturing processes, technology development, technological change forecast, production facilities, and quality control. The measurement reliability is excellent (Cronbach alpha = 0.96).

Marketing Capabilities. We use the scale items developed by Conant et al. (1990) to measure marketing capabilities. Respondents rated their SBU's knowledge of customers and competitors, integration of marketing activities, skills in segmentation and targeting, and effectiveness of pricing and advertising programs relative to the top three competitors in their industry on scales of 0 (much worse) to 10 (much better). The measurement reliability of these items is also excellent (Cronbach alpha = 0.93).

Information Technology Capabilities. Based on the literature (e.g., Day 1994, Bharadwaj et al. 1999), we developed a new scale of IT capabilities, designed to measure the capabilities that help an SBU create technical and market knowledge and facilitate communication flow across functional areas. Using 0 to 10 point scales as above, respondents were asked to rate the capabilities of their SBU's IT systems relative to the competition. For example, respondents had to rate their IT systems on ability to facilitate technology and market knowledge creation, to facilitate cross-functional integration, and to support internal and external communication. The coefficient Cronbach alpha for these scale items was 0.83, which indicates high measurement reliability.

Management Capabilities. Following Walker et al. (2003), we developed a set of six items measuring key management capabilities. Using 0 to 10 point scales, respondents rated their SBUs relative to their three major competitors on their abilities to integrate logistics systems, control costs, manage financial and human resources, forecast revenues, and manage marketing planning. These scale items have excellent measurement reliability (Cronbach alpha = 0.93).

3.2. Data Collection

Our data were derived from a large-scale survey of 800 randomly selected U.S. companies listed in *Ward's Business Directory*, the *Directory of Corporate Affiliations*, and the *World Marketing Directory*. We followed four distinct phases in our data collection: a presurvey, a survey on SBU strategies, a survey on relative capabilities, and phone/fax interviews for SBU information on performance data including profits and revenues. In the first stage, a one-page survey and an introductory letter was sent to selected firms requesting their participation and offering a set of research reports as an incentive to cooperate. Firms were asked to provide a contact person for a chosen, representative SBU/division. Of the 800 SBUs contacted, 392 agreed to participate and provided the necessary contacts at the SBU/division level (see DeSarbo et al. 2005 for details).

In the second stage, designated SBU managers received a questionnaire and a personalized letter. A three-wave mailing was used as recommended by Dillman (1978). Data on the measures of strategic types were obtained from 308 SBUs in this phase. We used the 11-item strategic-type scale previously developed and validated by Conant et al. (1990). In this phase, we also asked respondents to rate their confidence in their abilities to answer the questions thoroughly, and we eliminated individuals with low (below 6) levels of confidence from the final sample.

In the third stage, a questionnaire including the relative capability scales was sent to the SBU managers, again followed up by a three-wave mailing. At the end of this stage, we had complete data on relative capabilities and strategic types from a total of 216 SBUs, which represents a 27.0% response rate. The following industries were represented: computer-related products, electronics, electric equipment and household appliances, pharmaceuticals, drugs and medicines, machinery, telecommunications equipment, instruments and related products, airconditioning, chemicals and related products, and transportation equipment. Annual sales of sample SBUs ranged from $11 million to 750 million, and SBU size ranged from 100 to 12,500 employees.

We used the strategic-type data collected in the second stage to classify the 216 SBUs/divisions which responded to the third stage into the four M&S strategic types. We used the "majority-rule decision structure" of Conant et al. (1990) for this classification, with one modification: for an SBU to be classified as a prospector or a defender, it must have at least seven "correct" answers out of the 11 items. Using this procedure, we classified the 216 SBUs/divisions as follows: 62 *Prospectors*, 79 *Analyzers*, 59 *Defenders*, and 16 *Reactors*.

In the fourth and final stage, all 216 SBUs were contacted via phone or fax to obtain various performance data. We used two performance measures for this analysis. The short-term performance measure utilized was profitability, calculated as current-year gross margin divided by current-year total revenues. A longer-term performance measure utilized was ROI, defined as the return on investments made by the SBU over the past three years.[1]

4. The Constrained Finite-Mixture Structural-Equation Model

We employ a finite-mixture structural-equation approach to model the potential heterogeneity concerning firm strategic capabilities, performance, and

[1] Full details of the interview procedure and the questionnaire are available from the authors.

their interrelationships. To capture firm heterogeneity, we use a finite-mixture approach that derives *latent* strategic types wherein firms are homogeneous in terms of their underlying model parameters. Unlike previous multivariate finite-mixture procedures (e.g., Jedidi et al. 1997), our proposed methodology has a number of unique features that have been tailored for this particular application. First, it allows the response parameters to be constrained (e.g., nonnegative). This is an important feature in situations where theory imposes certain constraints on the parameters and/or the data suffer from multicollinearity problems. In the latter situations, it is well known that multicollinearity would lead to imprecise estimates as well as sign reversal. Second, we permit "external analyses" where, for example, models for rival taxonomies can be fit and tested. Finally, we provide a host of constrained versions of the model, where specific parameter subsets can be fixed at designated values for hypothesis testing of various nested models with certain aspects of heterogeneity fixed (via the use of equality rictions).

Let i index firms ($i = 1, \ldots, N$) and s denote membership in a (a priori unknown) strategic type ($s = 1, \ldots, S$). Let $\boldsymbol{\eta}_i^s$ be an $(M \times 1)$ vector of *latent* performance factors (e.g., profitability) for firm i in strategic type s and let $\boldsymbol{\xi}_i^s$ be a $(J \times 1)$ vector of *latent* firm capabilities (e.g., marketing, IT, management, etc.) and other exogenous unobserved factors. Conditional on membership in strategic type s, we postulate the following structural-equation model:

$$\boldsymbol{\eta}_i^s = \boldsymbol{\beta}_0^s + \mathbf{B}^s \boldsymbol{\xi}_i^s + \boldsymbol{\varsigma}_i^s, \tag{1}$$

where $\boldsymbol{\beta}_0^s = (\beta_{01}^s, \ldots, \beta_{0M}^s)'$ is an $(M \times 1)$ vector of intercept parameters, $\mathbf{B}^s = (\boldsymbol{\beta}_1^s, \boldsymbol{\beta}_2^s, \ldots, \boldsymbol{\beta}_M^s)'$ is an $(M \times J)$ matrix of regression parameters that capture the effects of latent firm capabilities $\boldsymbol{\xi}_i^s$ on latent performance factors $\boldsymbol{\eta}_i^s$, $\boldsymbol{\beta}_m^s = (\beta_{1m}^s, \ldots, \beta_{Jm}^s)'$ is a $(J \times 1)$ vector of regression parameters for the mth equation, and $\boldsymbol{\varsigma}_i^s$ is an $(M \times 1)$ vector of error terms assumed to follow a multivariate normal distribution with *null* mean vector and covariance matrix $\boldsymbol{\Psi}^s$. As firm capabilities are expected to impact performance positively, all the regression coefficients are constrained to be nonnegative (i.e., $\beta_{jm}^s \geq 0$; $1 \leq j \leq J$; $1 \leq m \leq M$). Assume that $\boldsymbol{\xi}_i^s$ follows a multivariate normal distribution with mean vector τ_ξ^s and covariance matrix Φ_ξ^s and is independent of $\boldsymbol{\varsigma}_i^s$. Then, $\boldsymbol{\eta}_i^s$ follows a multivariate normal distribution with (implied) mean vector

$$\boldsymbol{\tau}_\eta^s = \boldsymbol{\beta}_0^s + \mathbf{B}^s \boldsymbol{\tau}_\xi^s \tag{2}$$

and covariance matrix

$$\Phi_\eta^s = \mathbf{B}^s \Phi_\xi^s (\mathbf{B}^s)' + \boldsymbol{\Psi}^s. \tag{3}$$

Let $\mathbf{y}_i \mid s$ be a $(p \times 1)$ vector of *observed* performance measures (e.g., profitability, ROI) and $\mathbf{x}_i \mid s$ is a $(q \times 1)$ vector of *observed* firm capabilities measures (e.g., marketing, management, IT) for firm i in strategic type s. Then, the latent exogenous and endogenous factors $\boldsymbol{\xi}_i^s$ and $\boldsymbol{\eta}_i^s$ are related to observed capability and performance measures by the following measurement models:

$$\mathbf{x}_i \mid s = \boldsymbol{\Lambda}_x^s \boldsymbol{\xi}_i^s + \boldsymbol{\delta}_i^s, \tag{4}$$

$$\mathbf{y}_i \mid s = \boldsymbol{\Lambda}_y^s \boldsymbol{\eta}_i^s + \boldsymbol{\varepsilon}_i^s, \tag{5}$$

where $\Lambda_y^s(p \times M)$ and $\Lambda_x^s(q \times J)$ are factor loading matrices and $\varepsilon_i^s(p \times 1)$ and $\delta_i^s(q \times 1)$ are vectors of measurement errors in $\mathbf{y}_i \mid s$ and $\mathbf{x}_i \mid s$, respectively. Suppose that $\boldsymbol{\varepsilon}_i^s$ and $\boldsymbol{\delta}_i^s$ follow independent multivariate normal distributions with *zero* mean vectors and diagonal covariance matrices $\boldsymbol{\Theta}_\varepsilon^s(p \times p)$ and $\boldsymbol{\Theta}_\delta^s(q \times q)$, respectively. Then, the joint $((p+q) \times 1)$ vector

$$\boldsymbol{\Delta}_i \mid s = \begin{bmatrix} \mathbf{y}_i \mid s \\ \mathbf{x}_i \mid s \end{bmatrix}$$

has a multivariate normal distribution with mean vector

$$\boldsymbol{\mu}_s = \begin{bmatrix} \boldsymbol{\Lambda}_y^s \tau_\eta^s \\ \boldsymbol{\Lambda}_x^s \tau_\xi^s \end{bmatrix} \tag{6}$$

and covariance matrix

$$\Sigma_s = \begin{bmatrix} \boldsymbol{\Lambda}_y^s \Phi_\eta^s (\boldsymbol{\Lambda}_y^s)' + \Theta_\varepsilon^s & \boldsymbol{\Lambda}_y^s B^s \Phi_\xi^s (\boldsymbol{\Lambda}_x^s)' \\ \boldsymbol{\Lambda}_x^s \Phi_\xi^s (B^s)' (\boldsymbol{\Lambda}_y^s)' & \boldsymbol{\Lambda}_x^s \Phi_\xi^s (\boldsymbol{\Lambda}_x^s)' + \Theta_\delta^s \end{bmatrix}. \tag{7}$$

Assuming that the strategic types are unobserved, then the unconditional distribution of the observed vector

$$\boldsymbol{\Delta}_i = \begin{bmatrix} \mathbf{y}_i \\ \mathbf{x}_i \end{bmatrix}$$

is a finite mixture of these S distributions. That is,

$$\boldsymbol{\Delta}_i \sim \sum_{s=1}^{S} w_s f_s(\boldsymbol{\Delta}_i \mid \boldsymbol{\mu}_s, \boldsymbol{\Sigma}_s), \tag{8}$$

where $\mathbf{w} = (w_1, \ldots, w_S)'$ is the vector of the S mixing proportions such that $w_s > 0$ and $\sum_s^S w_s = 1$, and $f(\bullet)$ is the conditional multivariate normal density function $\mathrm{MVN}(\boldsymbol{\mu}_s, \boldsymbol{\Sigma}_s)$. One can see from Equations (6) and (7) how the proposed model captures various sources of heterogeneity. The S strategic types are heterogeneous with respect to the strategic capabilities means (τ_ξ^s), performance means (τ_η^s), the relationship between strategic capabilities and performance ($\boldsymbol{\beta}_0^s, \mathbf{B}^s$), and the measurement model parameters (Λ_y^s and Λ_x^s).

The corresponding likelihood function for a random sample $(\boldsymbol{\Delta}_1, \ldots, \boldsymbol{\Delta}_N)$ of N observations is then

$$L_S = \prod_{i=1}^{N} \sum_{s=1}^{S} w_s f_s(\boldsymbol{\Delta}_i \mid \boldsymbol{\mu}_s, \boldsymbol{\Sigma}_s), \tag{9}$$

where L_S is a function of the parameters w_s, $\mathbf{B}^s$, $\boldsymbol{\beta}_0^s$, $\boldsymbol{\Psi}^s$, $\boldsymbol{\Lambda}_y^s$, $\boldsymbol{\Lambda}_x^s$, $\boldsymbol{\Theta}_\varepsilon^s$, $\boldsymbol{\Theta}_\delta^s$, and $\boldsymbol{\Phi}_\xi^s$ $(s = 1, \ldots, S)$. The problem is to maximize L_S (or $\log L_S$) with respect to these parameters given sample data and the pre-specified number of strategic types S, while taking into account the constraints imposed on $\mathbf{w}$ and $\beta_{jm}^s \geq 0$; $1 \leq j \leq J$; $1 \leq m \leq M$ above. The appendix outlines the model estimation procedure.[2]

4.1. Nested Models

The structural-equation model described by Equations (1), (4), and (5) subsumes a variety of models as special cases. If all variables are measured without error, the model reduces to a finite-mixture simultaneous-equation model. If all variables are exogenous and error free, the model reduces to a finite mixture of multivariate normal distributions (in this case, $\Lambda_x^s = \mathbf{I}$ and $\boldsymbol{\Theta}_\delta^s = \mathbf{0}$). Reducing the model to either Equation (4) or (5) produces a finite-mixture confirmatory-factor analysis model. To determine the appropriate sources of heterogeneity defining the derived strategic types, we allow the testing for invariance of certain parameters across strategic types. For example, we can make the measurement model parameters invariant across strategic types (i.e., $\Lambda_y^s = \Lambda_y$ and $\Lambda_x^s = \Lambda_x$, $s = 1, \ldots, S$) if it is reasonable to assume that the groups react similarly to the measuring instrument for η^s and ξ^s. Likewise, we can impose invariance across groups on the covariance matrix of the exogenous factors $(\Phi_\xi^s = \Phi_\xi)$ and the covariance matrices of the error terms (i.e., $\boldsymbol{\Theta}_\varepsilon^s = \boldsymbol{\Theta}_\varepsilon$ and $\boldsymbol{\Theta}_\delta^s = \boldsymbol{\Theta}_\delta$). We can impose several other model restrictions depending on the context being studied and the particular theory or hypotheses being tested. For example, if the endogenous and exogenous factors are all measured with single indicators, then we must set $\boldsymbol{\Lambda}_y^s = \mathbf{I}$, $\boldsymbol{\Lambda}_x^s = \mathbf{I}$, $\boldsymbol{\Theta}_\varepsilon^s = \mathbf{0}$, and $\boldsymbol{\Theta}_\delta^s = \mathbf{0}$. In such ways, we can utilize likelihood ratio tests (LRT) *conditioned on* S to examine the sources of heterogeneity producing the derived strategic groupings. For example, models can be estimated where $\mathbf{B}^s = \mathbf{0}$ for $s = 1, \ldots, S$, indicating no relationship between the exogenous and endogenous variables once strategic types are controlled for. Or, one could estimate solutions where $\mathbf{B}^s = \mathbf{B}$ for all $s = 1, \ldots, S$ (i.e., there is no difference across derived strategic types in the relationships between strategic capabilities and performance). As we will show in the next section, such likelihood ratio tests to examine the significance of these nested models versus the full model can be gainfully employed to uncover the important aspects of the structure of the empirical data producing the strategic types. We see this as an important bonus to our modeling effort as the M&S approach offers no such diagnostics in their conceptual classification. As such, we can identify the significant sources of heterogeneity required to estimate strategic types empirically.

4.2. Model Selection

In general, the number of strategic types S is not known a priori. A number of model selection heuristics has been suggested to determine S for such finite-mixture models. Bozdogan (1994) proposed using a "modified" Akaike's (1974) information criterion (AIC) defined by

$$\text{MAIC}_S = -2 \ln L_S + 3N_S, \tag{10}$$

where N_S is the number of free parameters. Recently, Andrews and Currim (2003) found that the MAIC outperforms other model selection heuristics such as AIC, BIC, CAIC, and ICOMP (cf. Wedel and Kamakura 2000 for formulas) in terms of accurately identifying regression mixture model components. We shall use this criterion for determining the number of groups in our application.[3] We also use an entropy measure to gauge how well the groups are separated. A value close to one (zero) indicates excellent (poor) separation among the strategic types.

Note that we have programmed our estimation procedure to also accommodate "external analyses" for comparative hypothesis testing and model comparisons. For example, one can test a derived solution against any proposed alternative solution (e.g., the M&S typology), and utilize the information heuristics to designate which solution was "better" fit for the data. That is, given an alternative, pre-specified taxonomy of firms, one can fix the (posterior) probabilities of membership ($\pi_{is} = 1$ if firm i belongs to strategic type s and $\pi_{is} = 0$ otherwise; see the appendix), average them to obtain estimates of the mixing proportions, and just use the M-Step of the E-M algorithm to obtain estimates for $\mathbf{B}^s$, $\boldsymbol{\beta}_0^s$, $\boldsymbol{\Psi}^s$, $\boldsymbol{\Lambda}_y^s$, $\boldsymbol{\Lambda}_x^s$, $\boldsymbol{\Theta}_y^s$, $\boldsymbol{\Theta}_x^s$, and $\boldsymbol{\Phi}_\xi^s$ for each designated strategic type s. We will utilize this handy feature to compare our solution with the M&S typology as a special nested case of the full model.

[2] The proposed finite-mixture model is identified if the structural and measurement models in Equations (1), (4), and (5) are identified (see Bollen 1989, pp. 88–103, 238–246; Jedidi et al. 1997; and Hennig 2000).

[3] We need to run the procedure for varying values of S and pick the solution with minimum MAIC.

5. Empirical Results

We estimate the following model while varying the number of strategic types (S) from one through five:

$$\text{PROFIT}_i \mid s = \beta^s_{01} + \beta^s_{11}\text{MKT}_i + \beta^s_{21}\text{TECH}_i + \beta^s_{31}\text{MLINK}_i + \beta^s_{41}\text{INFTECH}_i + \beta^s_{51}\text{MGT}_i + \varsigma^s_{i1},$$

$$\text{ROI}_i \mid s = \beta^s_{02} + \beta^s_{12}\text{MKT}_i + \beta^s_{22}\text{TECH}_i + \beta^s_{32}\text{MLINK}_i + \beta^s_{42}\text{INFTECH}_i + \beta^s_{52}\text{MGT}_i + \varsigma^s_{i2},$$

where $\boldsymbol{\varsigma}^s_i = (\varsigma^s_{i1}, \varsigma^s_{i2})'$ follows a bivariate normal distribution with a zero mean vector and a covariance matrix $\boldsymbol{\psi}^s$ that varies across strategic types. MKT_i, TECH_i, MLINK_i, INFTECH_i, and MGT_i denote the marketing, technology, market linking, IT, and management capabilities (exogenous) factors, respectively. Given the relatively small sample size of firms, we use the first principal component scores derived within each set of capability items as measures for these exogenous factors.[4] In addition, we set the covariance matrix of the exogenous factors to be invariant across groups (i.e., $\Phi^s_\xi = \Phi_\xi$, $s = 1, \ldots, S$). Thus, conditional on membership in segment s, the vector $\boldsymbol{\xi}^s_i = (\text{MKT}_i, \text{TECH}_i, \text{MLINK}_i, \text{INFTECH}_i, \text{MGT}_i)' \mid s$ follows a multivariate normal distribution with mean vector $\boldsymbol{\tau}_s$ and covariance matrix Φ_ξ.[5]

5.1. Aggregate $S = 1$ Results

We begin by estimating the overall relationship between firm capabilities and profitability/ROI for the full sample ($S = 1$). This analysis is equivalent to estimating an ordinary regression model as long as all the coefficients remain nonnegative.[6] Table 1 shows that, overall, technology capabilities are most strongly related to performance. Four of the five capabilities (technology, IT, marketing, and market linking) are significantly related to profit, while only technology is significantly related to ROI. Thus, overall, the drivers of profit and ROI appear to be different: IT, market linking, and marketing are significantly related to the shorter-term profit measure, but not to the longer-term ROI performance measure.

Table 1 The Aggregate Complete Sample Solution

Capabilities	Profit	ROI
Intercept	0*	0
Marketing capabilities	**0.162**	0.084
Technology capabilities	**0.436**	**0.587**
Market linking capabilities	**0.156**	0.080
IT capabilities	**0.285**	0.006
Management capabilities	0.021	0.001
Error variance	**0.658**	**0.638**
Error covariance**	−0.003	
Error correlation	−0.005	

Note. All estimates in bold are significant ($p < 0.5$).
*All variables are standardized to zero mean and unit variance.
**Denotes the covariance between the Profit and ROI error terms.

5.2. The Constrained Finite-Mixture Structural-Equation Model Results

The aggregate $S = 1$ solution suggests that, overall, technology-related capabilities are most closely related to performance, and that the drivers of profit and ROI performance are somewhat different (at least for this sample of U.S.-based firms). These conclusions ignore heterogeneity and the possibility of strategic types; that is, they leave unaddressed the issue of whether different capabilities are more critical to performance than others for different groups or types of firms. To investigate this, we analyze this set of firms using our proposed methodology which explicitly models the observed relationships between capabilities and performance, as well as the mean levels of each, and choose the "best" solution using the MAIC model selection heuristic.

Table 2 presents a summary of the various goodness-of-fit heuristics for our proposed methodology as applied to this data set. The analysis was performed in $S = 1$, 2, 3, 4, and 5 strategic types, with the MAIC heuristic designating $S = 4$ derived strategic types as the "optimal" solution with an entropy of 0.86, which indicates that the derived groups are well separated.

For comparison, we classify the firms into the M&S strategic types according to the Conant et al. (1990) schema and perform an "external analysis." The 11-item scale for each of the four strategic types was directly adopted from Conant et al. (1990). We classified SBUs as *Prospector, Analyzer, Defender*, or *Reactor* using the "majority-rule decision structure" (see

[4] With a small sample size of 216 firms, it is impossible to estimate all the parameters of the finite-mixture structural-equation model. In the context of our study, a fully specified structural-equation model would require the estimation of 84 parameters per group excluding the mixing proportions (22 factor loadings, 27 error variances, five factor means, 15 exogenous factor variance and covariance elements, three structural variance-covariance elements, and 12 regression coefficients). The number of parameters would be still high even if we impose across-group invariance restrictions on certain parameters. As suggested by one anonymous reviewer, the limitation of using the first principal component of a separate factor analysis is that the errors in the estimated factor scores are ignored in the second-stage analysis. In addition, model fit is likely to be worse because traditional factor analysis assumes common population parameters. The component scores are derived using principal component analysis.

[5] To avoid local optima problems, we have estimated each model at least 20 times using different random starting values and we selected the solution with the best log-likelihood value. On average, about 70% of the runs converged to the largest stationary maximum which suggests that the solutions we report are likely to be global optima.

[6] Note that the standard errors may be different, especially when the parameters are close to the boundary conditions. This is because the Hessian is affected by restrictions on the parameters.

Table 2 Model Selection Heuristics

Number of groups	# of parameters	Minus log-likelihood	MAIC	Entropy
1	35	2,165.5	4,436.0	1.00
2	56	1,993.5	4,155.0	0.88
3	77	1,972.3	4,175.6	0.76
4	98	1,898.1	**4,090.2**	0.86
5	119	1,879.3	4,115.6	0.86
Miles and Snow strategic types (our model)*	95	2,001.0	4,287.0	1.00
Miles and Snow strategic types (MVN mixture)**	56	2,033.8	4,235.6	1.00

Note. The number in bold denotes minimum values for MAIC.

*This row reports the goodness-of-fit statistics for our model given the M&S typology.

**Goodness-of-fit statistics for a mixture of multivariate normals given the M&S typology.

Table 3 Nested Model Comparisons

Alternative models	# of parameters	Minus log-likelihood	LRT*	Entropy
Unrestricted model	98	1,898.1		0.86
Null beta coefficients	58	1,959.4	**122.6**	0.84
Fixed beta coefficients	59	1,963.2	**130.2**	0.82
Fixed exogenous means	78	1,955.6	**115.0**	0.71

*LRT denotes the likelihood ratio test statistic. All statistics in bold are significant ($p < 0.01$).

Conant et al. 1990 for details), which requires six "correct" responses on the scale. We compare the fit of the M&S solution with the empirically-derived solution to assess if any marginal improvement can be gained by using the empirically-derived strategic typology for this sample. The results in Table 2 (the last two rows) show that *all* of the empirically-derived solutions dominate the M&S strategic typology in terms of this information heuristic.[7] Thus, while insights can be gained about the relationships between capabilities and performance by examining the results from the M&S typology, an even more accurate picture of the strategies employed by these firms and their resulting performance can be obtained from the empirically-derived classification scheme. We also use the M&S typology to fit a finite mixture of multivariate normal distributions (see §4.2) and compare its fit to that from our model. Again, the MAIC heuristic favors the derived full model (see Table 2).

To determine the sources of heterogeneity that are driving our $S = 4$ solution, we estimated a series of nested and nonnested models. Table 3 presents the results for the nested models. The "null beta coefficients" solution constrains $\mathbf{B}^s = \mathbf{0}$ for all $s = 1, \ldots, S$, but allows the intercepts and the firm capabilities means to vary freely across groups. This model assumes that, given membership in a latent strategic type, firms' capabilities have no impact on performance. Thus, all firms within a specific strategic type are homogeneous with respect to *both* firm capabilities and performance factors. Firms in different strategic types are heterogeneous with respect to the mean levels of these variables. Although statistically derived, this particular typology is consistent with that of M&S: All firms within a strategic type have the same capabilities and are expected to perform equally. As shown by the likelihood ratio test (LRT versus the full model), this nested model is rejected. Thus, firm capabilities do have an impact on performance. The issue is whether such an impact is the same or different across strategic types.

To check whether the impact of firm capabilities on performance is invariant across strategic types, we tested the "fixed beta coefficients" model which constrains $\mathbf{B}^s = \mathbf{B}$ for all $s = 1, \ldots, S$, but allows for varying intercepts and varying firm capability means. Unlike the "null beta coefficients" model, this model allows firm capabilities to impact firm performance but constrains this relationship to be invariant across strategic types. Thus, firms in different strategic types have different base levels of performance (different intercepts) and different levels of firm capabilities. Using LRT, this nested model is also rejected. Thus, firm capabilities do have a differential impact across strategic types. This suggests that not only the capabilities themselves make firms perform better, but also the ability of firms to utilize these capabilities to perform better.[8] Therefore, unlike the M&S typology, two firms with same levels of capabilities can have different levels of performance. This is consistent with the RBV which suggests that differences in managerial actions account for different performance levels among comparable SBUs.

For our model comparisons to be exhaustive, we need to examine whether only the exogenous or the endogenous variables are driving the grouping of firms. We tested two other models: The "fixed exogenous means" model and the "fixed performance means" model. The former model allows all the beta coefficients (including the intercepts) to vary across strategic types but constrains the means of the firm capabilities to be invariant. This means that firms in different strategic types have the same mean capabilities and that differences in performance are due to differences in the impact of the capabilities factors across

[7] This is expected because the M&S typology is formed solely on the basis of capabilities. In addition, the typology is derived subjectively based on a set of questions and not on the basis of a likelihood function.

[8] An alternative view is that there are unobserved factors that moderate the relationship between performance and capabilities. The different environments faced by firms or the firms' latent abilities to use their strategic capabilities to maximum advantage are examples of such unobserved factors.

Table 4 The Miles and Snow Strategic-Type Solution

	Prospectors		*Analyzers*		*Defenders*		*Reactors*	
Capabilities	Profit	ROI	Profit	ROI	Profit	ROI	Profit	ROI
Intercept	0.403	−0.240	−0.026	0.016	**−0.356**	0.321	−1.297	0.218
Marketing capabilities	0.069	0.043	0.182	0.000	**0.239**	0.264	0.018	0.333
Technology capabilities	**0.587**	**0.378**	**0.512**	**0.728**	0.198	**0.805**	0.058	0.468
Market linking capabilities	0.079	0.282	0.120	0.000	**0.494**	0.000	0.056	0.000
IT capabilities	0.101	0.129	0.091	0.047	0.001	0.341	0.037	0.036
Management capabilities	0.000	0.000	0.079	0.142	0.096	0.000	0.000	0.490
Error variance	**0.720**	**0.499**	**0.462**	**0.532**	**0.236**	**0.550**	0.179	0.296
Error covariance*	0.064		0.144		0.081		0.177	
Error correlation	0.107		0.290		0.225		0.769	
Mixing proportions**	0.287		0.366		0.273		0.074	

Note. All variables are standardized to have zero mean and unit variance for the entire sample. All estimates in bold are significant ($p < 0.5$).

*Denotes the covariance between the Profit and ROI error terms.

**These proportions are externally provided.

the strategic types. This solution is rejected by the LRT versus the full model (see Table 3) which suggests that both the level and impact of the exogenous, capability factors are significant drivers of the firm groupings. The "fixed performance means" model constrains the means for the two performance variables to be equal across derived strategic types.[9] That is, strategic types are formed on the basis that they do not vary with respect to the way they perform. Technically, this nonnested model represents a finite mixture of multivariate normal distributions where the capability factor means are allowed to vary across strategic types, but the performance means are constrained to be invariant. The log-likelihood for this model is −2,036.8 and the entropy is only 0.511, suggesting poor separation between the groups. Using the MAIC criterion, this solution is also rejected (MAIC = 4,223.6).

Thus, it appears that for this particular data set, one needs to explicitly consider heterogeneity with respect to both sets of variables (endogenous and exogenous), as well as the relationships between the two to derive appropriate strategic types. All three components are necessary in properly accounting for the sources of heterogeneity in deriving the four strategic types for this particular data set.

5.3. External Analysis: The Miles and Snow Strategic Types

We first examine the external analysis results by strategic type using the M&S typology. The results in Table 4 show that somewhat different relationships between capabilities and performance exist for each strategic type. For *Prospectors* and *Analyzers*, technology is most strongly related to both profit and ROI, while for *Defenders*, the capabilities most significantly related to profit are marketing and market linking. These findings are in line with expectations from the M&S typology, although some results were surprising. For example, technology was significantly related to ROI for *Defenders*, but IT and market linking were not. One might expect from the M&S typology that for *Analyzers*, both technology and marketing skills should be significantly related to profit, but in fact only technology skills were found to be significant. No significant relationships were found between capabilities and profit or ROI for *Reactors*.[10] We conclude that the drivers of profit and ROI appear to be somewhat different across M&S types.

Table 5 displays the estimated factor means for the four M&S strategic types. As predicted by M&S, firms following any of the three archetypal strategic types outperform *Reactors*: the raw (unstandardized) profit (not shown in Table 5) of *Prospectors*, *Analyzers*, and *Defenders* was 14.71, 7.34, and 5.81 respectively, while the mean profit for *Reactors* was −8.48. Of course, the standardized profits of the four types reported in Table 5 showed the same result: *Reactors* were outperformed by all other types. Interestingly, this expectation was not confirmed for ROI performance, which was not shown to differ substantially across the four types.[11]

Examining the mean capability scores for each strategic type, we find the following:

- *Prospectors* have the highest standardized mean scores on technology and IT capabilities, and one of the highest standardized mean scores on management

[9] We do not report this model in Table 3 because it is not nested.

[10] The lack of significant coefficients in this group is primarily due to the small sample size for *Reactors* (16 firms).

[11] Because profitability is reported as a one-year profit figure and ROI is reported over a three-year time period, it is possible for an SBU to show negative profit and positive ROI.

Table 5 Estimated Factor Means for Miles and Snow Strategic Types

Variable	*Prospectors*	*Analyzers*	*Defenders*	*Reactors*
Marketing capabilities	−0.265	−0.109	**0.501**	**−0.280**
Technology capabilities	0.240	−0.008	−0.207	**−0.131**
Market linking capabilities	−0.346	0.062	0.255	0.094
IT capabilities	0.645	−0.017	−0.428	−0.832
Management capabilities	0.119	0.013	−0.181	0.146
Profit*	0.563	−0.043	−0.169	−1.335
ROI	−0.175	0.012	0.141	0.105

Note. All estimates in bold are significantly different from zero ($p < 0.05$).
*The statistical significance of the endogenous variables means cannot be established because the means of these variables are implied by the model (see Equation (2)).

capabilities. *Prospectors* have low scores on marketing and market linking capabilities. Note that the differences are only statistically significant in the cases of marketing and technology capability.

- *Defenders* are the polar opposites of *Prospectors*. They have the highest standardized mean scores on marketing and market linking capabilities, and lower scores on technology, IT, and management. Again, only the marketing capability differences are significant.
- *Analyzers* have standardized mean scores midway between *Prospectors* and *Defenders* on each of the five capability scales. This is as expected by M&S, although the differences are not always statistically significant.
- *Reactors* score among the lowest on all capabilities except market linking and management. In the case of marketing and technology capabilities, *Reactors* score significantly lower than other strategic types.
- *Prospectors* show the highest short-term performance but *Defenders* have the highest ROI.

5.4. The Derived "Mixed-Type" Strategic Group Solution

Next, we examine the finite-mixture structural-equation model estimates for the relative importance of firm capabilities by strategic type for the derived, "mixed-type" solution. We characterize our solution as "mixed-type" as each derived group, as to be shown shortly, is composed of a mix of M&S strategic types. Table 6 clearly shows a different set of significant relationships between firm capabilities and performance. For Strategic Type 1, IT has the greatest impact on profit, while technology and market linking capabilities have a greater impact on ROI. Four of the five capabilities (marketing, technology, market linking, and management) significantly affect profit for Strategic Type 2, although none of the capabilities has a significant impact on ROI. For Strategic Type 3, the most significant influences on profit are technology, market linking, and management, although all five capabilities have significant influences on profit, but only marketing significantly impacts ROI. Finally, Strategic Type 4 shows yet another different pattern: technology and marketing influence profit, while IT influences ROI.

Table 7 reports the estimated means of exogenous and endogenous factors by strategic type. This information provides additional insight for interpreting the derived strategic types. Strategic Type 1 has the highest standardized mean in technology capability, and is second-highest in market linking, IT, and management capabilities. Strategic Type 2, conversely, is highest in marketing, market linking, and management capabilities. Strategic Type 3 is highest in IT capability but scores relatively low in all other capabilities. Strategic Type 4 is higher in market linking and management capability than Strategic Type 3. Analysis of the endogenous variable means shows that Strategic Type 1 outperforms all other types on

Table 6 The Derived Four Strategic-Type Solution

	Group 1		Group 2		Group 3		Group 4	
Capabilities	Profit	ROI	Profit	ROI	Profit	ROI	Profit	ROI
Intercept	−0.009	−0.135	**−0.912**	**−1.059**	−0.006	−0.240	**1.297**	0.268
Marketing capabilities	0.000	0.091	**0.510**	0.000	**0.148**	**0.666**	**0.333**	0.028
Technology capabilities	0.363	**0.759**	**0.418**	0.000	**0.484**	0.000	**1.555**	0.503
Market linking capabilities	0.113	**0.257**	**0.339**	0.064	**0.248**	0.092	0.089	0.028
IT capabilities	**0.497**	0.000	0.000	0.262	**0.167**	0.000	0.266	**0.447**
Management capabilities	0.066	0.103	**0.230**	0.174	**0.228**	0.000	0.000	0.000
Error variance	**0.575**	**0.403**	**0.050**	**0.111**	**0.078**	**0.245**	**0.551**	**0.387**
Error covariance*	−0.110		0.017		**0.069**		**−0.208**	
Error correlation	−0.229		0.224		**0.498**		**−0.451**	
Mixing proportions	**0.310**		**0.142**		**0.275**		**0.272**	

Note. All variables are standardized to have zero mean and unit variance for the entire sample. All estimates in bold are significant ($p < 0.5$).
*Denotes the covariance between the Profit and ROI error terms.

Table 7 Estimated Means of Exogenous and Endogenous Variables by Derived Strategic Type

Variable	Group 1	Group 2	Group 3	Group 4
Marketing capabilities	−0.017	**0.776**	−0.034	**−0.351**
Technology capabilities	**1.244**	**−0.539**	**−0.417**	**−0.713**
Market linking capabilities	0.131	0.320	−0.231	−0.083
IT capabilities	0.093	−0.085	0.109	−0.172
Management capabilities	0.191	0.441	−0.324	−0.119
Profit*	0.516	−0.532	−0.325	0.018
ROI	0.860	−0.984	−0.284	−0.180

Note. All estimates in bold are significantly different from zero ($p < 0.05$).
*The statistical significance of the endogenous variables means cannot be established because the means of these variables are implied by the model (see Equation (2)).

both profit and ROI, followed by Types 4 and 3, respectively, and Strategic Type 2 shows the poorest performance.

We now explore the correspondence between the M&S typology and our typology. As Table 8 depicts, Strategic Type 1 (the highest-performing type) is comprised of roughly one-third *Prospectors* and one-third *Analyzers*. There are slightly fewer *Defenders*, and a small number of *Reactors*. Interestingly, Strategic Type 4 (the second-highest performing type) has almost the same distribution of M&S types: one-third each of *Prospectors* and *Analyzers*, with the remainder being *Defenders* and *Reactors*. Strategic Types 2 and 3 (the lowest-performing types) are comprised of almost one-half *Analyzers*, with proportionately less *Defenders* and *Prospectors*.

Taking all the information presented in Tables 6 and 7 (as well as computing raw scale item means which we do not show to save space), we can finally develop descriptions of each of the four empirically-derived strategic types.

Strategic Type 1: New Product/Market Seekers with Technology Strengths. This strategic type has a large number of *Prospector* and *Analyzer* firms, as well as several of the more aggressive *Defenders*. Typical of *Prospectors*, members of this strategic type have notable strengths in technology, in particular, new product development. They also have strengths in IT, particularly IT that supports new product development, cross-functional integration, and technology knowledge creation. Judging from the performance measures, Strategic Type 1 seems to be able to reap short-term profitability and also to translate new product success into superior longer-term ROI performance.

Strategic Type 2: Defensive Firms with Marketing Strengths. Unique among the four strategic types, this type is made up largely of *Analyzers* and *Defenders*. Typical of *Defenders*, this type tends to excel in marketing, including information gathering, segmenting and targeting markets, pricing, and advertising. It also tends to be strong in management capabilities, including financial management, human resource planning, marketing planning, and logistics. Despite these capabilities, however, this strategic type is outperformed by other SBUs in terms of both short-term profit and long-term ROI measures.

Strategic Type 3: Second-But-Better Firms with IT Strengths. This group seems to be most closely aligned with *Analyzers*, who use their second-but-better strategies and capabilities in IT (in particular, IT to support new product development, cross-functional integration, and technology knowledge creation) to get a competitive edge. This strategy type is second only to Strategic Type 1 on all of these IT capabilities. This type's profit performance, however, is relatively low, surpassing only Strategic Type 2 in terms of both profit and ROI.

Strategic Type 4: New Product/Market Seekers with Market Linking and Management Strengths. Like Strategic Type 1, this type is comprised mostly of *Analyzers* and *Prospectors*, with many *Defenders* as well. Whereas Strategic Type 1 is strong in both IT and technology capabilities, Strategic Type 4 is noticeably weaker in technology capabilities, but is in the middle of the pack in terms of other capabilities. What distinguishes this strategic type from the poorer-performing Strategic Type 3 is relative strength in market linking and management capabilities. Strategic Type 4 is the second-best performing type in terms of both profit and ROI.

Table 8 Membership Cross-Classification

	Derived types				
Miles and Snow	1	2	3	4	Total
Prospectors	21	6	19	16	62
Analyzers	20	14	27	18	79
Defenders	18	8	18	15	59
Reactors	6	3	0	7	16
Total	65	31	64	56	216

5.5. Validity Assessment

It is extremely difficult to compare our typology and that of M&S in terms of external predictive validity. This is mainly because the sample size is small and each typology would require a priori knowledge of the strategic types for any SBUs in a holdout sample. In addition, it is difficult to find a neutral criterion for comparing both methods. However, to provide some evidence for validity, we have performed ANOVAs on the respective strategic types generated from each approach on a number of different performance criteria including market share, customer retention, sales growth, etc. As can be seen in Table 9, the M&S scheme

Table 9 ANOVA Results for Comparing the Means of Several Performance Measures Across Strategic Types

	Miles and Snow typology		Our typology		
Variable	*F*-statistic	*p*-value	*F*-statistic	*p*-value	Variable definition
PROFIT	**21.6**	**0**	**13.309**	**0**	(Total revenue – total variable costs)/total revenue
ROIPEC	1.07	0.36	**53.342**	**0**	The average ROI in this business unit over the past three years (in %)
ROI*	1.09	0.353	**54.148**	**0**	Return on investment
ROA*	0.64	0.59	**36.649**	**0**	Return on assets
RMS*	1.5	0.201	**44.201**	**0**	Relative market share
CUSRET*	0.97	0.406	**57.313**	**0**	Overall customer retention
CUSRET2*	0.93	0.426	**49.582**	**0**	Retention of major customers
SALESGR*	0.33	0.799	**45.592**	**0**	Sales growth
PERF1**	1.76	0.154	**36.471**	**0**	Overall profit margin relative to the objective for this business unit
PERF2**	1.39	0.245	**31.062**	**0**	Overall sales relative to the objective for this business unit
PERF3**	0.04	0.988	**50.171**	**0**	Overall return on investment relative to the objective for this SBU

Note. All *F*-statistics in bold are significant (i.e., variable means are significantly different across strategic types, $p < 0.001$).

The six scales marked by * were measured as follows: Please rate how well this business unit has performed relative to all other competitors in the principal served market segment over the past year.

0	1	2	3	4	5	6	7	8	9	10
0%	1%–10%	11%–20%	21%–30%	31%–40%	41%–50%	51%–60%	61%–70%	71%–80%	81%–90%	91%–100%

The three scales marked by ** were measured as follows: Please rate the extent to which your business unit has achieved the following outcomes during the last year (11-point scale, where 0 = low and 10 = high).

only renders significant differences with respect to profitability and none of the other measures. Our solution, however, renders significant differences with respect to all measures.

6. Discussion

The RBV of the firm has become a very popular conceptualization of SBU competitiveness. The RBV posits that firms or SBUs must possess key capabilities, and also deploy them strategically (i.e., put them to their best use), to create sustainable competitive advantage and achieve high levels of performance. The most popular typology of SBU strategy has remained that of Miles and Snow (1978) which has stood the test of time (Hambrick 2003) and is still widely used in academic research. Despite its important contributions to strategic management, the M&S typology has actively been criticized in the literature. It is predominantly descriptive in nature, lacking in consideration of environment and performance variables, and not necessarily applicable to industries other than those included in the original exploratory study. These limitations make it difficult to reconcile the M&S model with the more recent literature on strategic types and the RBV.

Our proposed methodology thus makes a theoretical contribution in that we adopt an RBV perspective and extend the M&S model to explicitly consider strategic capabilities, performances, and their interrelationships as the basis for deriving strategic types. We devised a constrained finite-mixture structural-equation methodology and empirically derived a four-group, "mixed-type" strategic typology. We find that our typology improves on the M&S typology in terms of statistical fit. The predictive methodology we devise here completely differs from DeSarbo et al. (2005) and allows us to capture the nature of heterogeneity among the firm capability and performance variables due to the estimation of a series of nested models. DeSarbo et al. (2005) identified associations between capabilities, strategies, performance, and strategic types. This study extends the prior findings by suggesting that strategic decision making by SBUs is context dependent: different capabilities lead to improved profit performance for different strategic types. This is in line with the expectations of the RBV. Thus, for different strategic types, different capabilities will be tied to performance.

Our typology also has important prescriptive implications for management, consistent with the expectations of the RBV. In particular, we recommend a contingency-driven strategic stance. SBU management needs to consider existing capabilities and the environmental context, then correctly choose which capabilities best complement the existing core competencies to improve profit performance. Scarce financial resources should be allocated to supporting and further improving these capabilities, so as to build sustainable competitive advantage and increase economic rent. Managers who recognize which capabilities best complement the existing set of competencies will be rewarded with higher performance levels. Management may even decide that its existing set of capabilities are in fact better suited to a different strategic type, and may use its scarce resources to build up the most appropriate set of complementary capabilities so as to compete more effectively.

In our study, we find that the M&S typology provides a limited means of strategic decision making, and can be improved on by including firm capabilities, measures of performance, and the interrelationships between the two. Our proposed methodology augments the M&S typology in that we found differences among the types that can be explained in terms of differences in strategic capabilities, performance, and the relationship between capabilities and performance. Our statistical tests indicated that all three components were necessary for accounting for the SBU heterogeneity encountered in this particular sample. One constellation of firm capabilities (Strategic Type 1) was linked to highest performance in both profit and ROI; a second set of firm capabilities was linked to the second-highest performance level (Strategic Type 4), while the other strategic types were also-rans. Another insight concerned the two highest performers, Strategic Types 1 and 4, taken together. Both of these were primarily (though not exclusively) made up of firms that were classified as *Prospectors* and *Analyzers* using M&S; there were proportionally fewer *Defenders* in each strategic type. The results suggest that there are two ways to success. The best-performing strategic type, Strategic Type 1, showed superior capabilities in technology and IT (which would be consistent with *Prospector* strategy), but was not necessarily weak in any of the other capabilities. Strategic Type 4, by contrast, did not have a profile consistent with *Prospector* strategy: these SBUs used fairly strong capabilities in IT, and good market linking capabilities, to offset weaknesses in technology and marketing capabilities and still be profitable. This insight was obscured when considering only the M&S solution. In sum, different combinations of firm capabilities seem to drive different measures of performance; and using the methodology described in this paper permitted greater insights into the complex relationships among the capability and performance variables. Our findings suggest that managers of the SBUs in the highest-performing strategic types are those that have done the best job in identifying which capabilities are strategically the best to allocate scarce financial resources to. Depending on strategic type, different SBUs will focus on improving different sets of capabilities.

There are certain limitations to our study. Methodologically, the proposed finite-mixture, structural-equation method requires data from large samples for complete and reliable estimation of the model parameters. This could be problematic, especially when collecting data from businesses. However, the estimation approach that we followed in this paper appears to be robust. Substantively, we are unable to confirm whether the strategic typology we derived is generalizable to other industries, countries, or geographical regions. An important benefit of our proposed methodology, however, is that one can empirically derive a strategic typology of firms or SBUs specific to *any* specified industry, given data availability. In addition, given this model-based empirical approach, once solution estimates have been obtained, managers can perform policy simulations to investigate the effects on performance of modifying strategic capabilities or their effectiveness in deployment. Extensions of this study could examine the specific strategic types found in other environmental contexts, or could also explore the effects of capabilities on other outcome variables, such as success at radical innovation. We believe that the proposed methodology can be successfully and flexibly used in understanding strategic decision making and performance outcomes in a wide range of contexts and industries.

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Appendix. Model Estimation

We formulate an E-M algorithm[12] to maximize the likelihood function in Equation (9). Let λ_{is} be a binary variable that indicates if firm i belongs to strategic type s. Assume that the latent vector $\boldsymbol{\lambda}_i = (\lambda_{i1}, \ldots, \lambda_{iS})'$ is i.i.d. multinomially distributed with probabilities $\mathbf{w}$. That is, $\boldsymbol{\lambda}_i \mid \mathbf{w} \sim \prod_{s=1}^{S} w_s^{\lambda_{is}}$. Then, the distribution of $\boldsymbol{\Delta}_i$ given $\boldsymbol{\lambda}_i$ is

$$\boldsymbol{\Delta}_i \mid \boldsymbol{\lambda}_i \sum_{s=1}^{S} \lambda_{is} f_s(\boldsymbol{\Delta}_i \mid \boldsymbol{\mu}_s, \boldsymbol{\Sigma}_s) = \prod_{i=1}^{S} [f_s(\boldsymbol{\Delta}_i \mid \boldsymbol{\mu}_s, \boldsymbol{\Sigma}_s)]^{\lambda_{is}}. \tag{A1}$$

Let $\boldsymbol{\mu} = (\boldsymbol{\mu}_1, \ldots, \boldsymbol{\mu}_S)$ and $\boldsymbol{\Sigma} = (\boldsymbol{\Sigma}_1, \ldots, \boldsymbol{\Sigma}_S)$. The complete-data, log-likelihood function is given by

$$\begin{aligned} &\log L_c(\boldsymbol{\mu}, \boldsymbol{\Sigma}, \mathbf{w} \mid \boldsymbol{\Delta}, \mathbf{L}) \\ &\quad = \frac{-(J-1)}{2} \log(2\pi) \sum_{i=1}^{N} \sum_{s=1}^{S} \lambda_{is} - \frac{1}{2} \sum_{i=1}^{N} \sum_{s=1}^{S} \lambda_{is} |\boldsymbol{\Sigma}_s| \\ &\qquad - \frac{1}{2} \sum_{i=1}^{N} \sum_{s=1}^{S} \lambda_{is} (\boldsymbol{\Delta}_i - \boldsymbol{\mu}_s)' \boldsymbol{\Sigma}_s^{-1} (\boldsymbol{\Delta}_i - \boldsymbol{\mu}_s) + \sum_{i=1}^{N} \sum_{s=1}^{S} \lambda_{is} \log(w_s). \end{aligned} \tag{A2}$$

The E-M algorithm maximizes (A2) by iterating between an E-step (where we compute the expected value of $\boldsymbol{\lambda}_i$ given $\boldsymbol{\Delta}$ and provisional estimates for $\boldsymbol{\mu}_s$, $\boldsymbol{\Sigma}_s$, and $\mathbf{w}$) and an M-step (where we maximize (A2) conditional on $\mathbf{L} = ((\lambda_{is}))$ to estimate all parameters) until convergence. We enforce positivity constraints by reparameterizing the relevant parameters as $\beta_{jm}^s = (\gamma_{jm}^s)^2$. Upon convergence, we compute the asymptotic standard errors using the inverse of the empirical information matrix by taking the second-order derivatives of the likelihood function in Equation (9) with respect to all model parameters including the mixing proportions. For the constrained parameters, the second-order

[12] Details on the E-M algorithm can be obtained from the authors; see also Wedel and Kamakura (2000).

derivatives are taken with respect to β^s_{jm}[13] and not γ^s_{jm}. We simultaneously assign firms to each of the S (latent) strategic types by using Bayes' rule:

$$\hat{\pi}_{is} = \frac{\hat{w}_s f_s(\Delta_i \mid \hat{\boldsymbol{\mu}}_s, \hat{\boldsymbol{\Sigma}}_s)}{\sum_{g=1}^{S} \hat{w}_g f_g(\Delta_i \mid \hat{\boldsymbol{\mu}}_g, \hat{\boldsymbol{\Sigma}}_g)}, \tag{A3}$$

where $\hat{\pi}_{is}$ denotes the estimated posterior probability that firm i belongs to strategic type s. These probabilities represent a fuzzy classification of the N firms into the S strategic types.

[13]The authors thank an anonymous reviewer for drawing our attention to this point.

References

Akaike, H. 1974. A new look at statistical model identification. *IEEE Trans. Automatic Control* **6** 716–723.

Amit, Raphael, Paul J. Schoemaker. 1993. Strategic assets and organizational rent. *Strategic Management J.* **14**(January) 33–46.

Andrews, R. L., I. S. Currim. 2003. Retention of latent segments in regression-based marketing models. *Internat. J. Res. Marketing* **20** 315–321.

Barney, Jay B. 1986. Strategic factor markets: Expectations, luck and business strategy. *Management Sci.* **32**(October) 1231–1241.

Barney, J. 1991. Firm resources and sustained competitive advantage. *J. Management* **17** 99–120.

Barney, Jay B., Edward J. Zajac. 1994. Competitive organizational behavior: Toward an organizationally-based theory of competitive advantage. *Strategic Management J.* **15** 5–9.

Bharadwaj, Anandhi S., Sundar G. Bharadwaj, Benn R. Konsynski. 1999. Information technology effects on firm performance as measured by Tobin's Q. *Management Sci.* **45**(7) 1008–1024.

Bollen, Kenneth A. 1989. *Structural Equations with Latent Variables.* Wiley, New York.

Bozdogan, H. 1994. Mixture model cluster analysis using model selection criteria and the new information measure of complexity. *Proc. First U.S.-Japan Conf. on the Frontiers of Statistical Modeling.* Kluwer Academic Publishers, Dordrecht, The Netherlands, 69–113.

Churchill, G. A., Jr. 1979. A paradigm for developing better measures of marketing constructs. *J. Marketing Res.* **16** 64–73.

Conant, Jeffrey S., Michael P. Mokwa, P. Rajan Varadarajan. 1990. Strategic types, distinctive marketing competencies and organizational performance: A multiple-measures-based study. *Strategic Management J.* **11** 365–383.

Davis, Fred D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quart.* **13**(3) 319–339.

Day, G. S. 1990. *Market Driven Strategy: Processes for Creating Value.* Free Press, New York.

Day, George S. 1994. The capabilities of market-driven organizations. *J. Marketing* **58**(4) 37–52.

Day, George S., Robin Wensley. 1988. Assessing advantage: A framework for diagnosing competitive superiority. *J. Marketing* **52**(2) 1–20.

DeSarbo, W. S., C. A. Di Benedetto, M. Song, I. Sinha. 2005. Revisiting the Miles and Snow strategic framework: Uncovering interrelationships between strategic types, capabilities, environmental uncertainty, and firm performance. *Strategic Management J.* **26**(1) 47–74.

Dierckx, I., K. Cool. 1989. Asset stock accumulation and sustainability of competitive advantage. *Management Sci.* **35**(12) 1504–1511.

Dillman, D. A. 1978. *Mail and Telephone Surveys: The Total Design Method.* Wiley, New York.

Griffin, Abbie, John R. Hauser. 1996. Integrating R&D and marketing: A review and analysis of the literature. *J. Product Innovation Management* **13**(2) 191–215.

Hambrick, Donald C. 1983. Some tests of the effectiveness and functional attributes of Miles and Snow's strategic types. *Acad. Management J.* **26**(March) 5–25.

Hambrick, Donald C. 1984. Taxonomic approaches to studying strategy: Some conceptual and methodological issues. *J. Management* **10**(1) 27–41.

Hambrick, Donald C. 2003. On the staying power of defenders, analyzers, and prospectors. *Acad. Management Executive* **17** 115–118.

Hennig, Christian. 2000. Identifiability of models for clusterwise linear regression. *J. Classification* **17** 273–296.

Hitt, Michael A., R. Duane Ireland. 1985. Corporate distinctive competence, strategy, industry, and performance. *Strategic Management J.* **6**(July–September) 273–293.

Hunt, Shelby D., Robert M. Morgan. 1995. The comparative advantage theory of competition. *J. Marketing* **59**(April) 1–15.

Jaworski, Bernard J., Ajay K. Kohli. 1993. Market orientation: Antecedents and consequences. *J. Marketing* **57**(3) 53–70.

Jedidi, K., H. Jagpal, W. DeSarbo. 1997. Semi-parametric structural equation models for response-based segmentation and unobserved heterogeneity. *Marketing Sci.* **16** 9–59.

McDaniel, Stephen W., James W. Kolari. 1987. Marketing strategy implications of the Miles and Snow strategic typology. *J. Marketing* **51**(4) 19–30.

Miles, R., C. Snow. 1978. *Organizational Strategy, Structure, and Process.* McGraw-Hill, New York.

Penrose, Edith. 1959. *The Theory of Growth of the Firm.* Blackwell Press, Oxford, UK.

Peteraf, Margaret A. 1993. The cornerstones of competitive advantage: A resource-based view. *Strategic Management J.* **14**(March) 179–191.

Shortell, S. M., E. J. Zajac. 1990. Perceptual and archival measures of Miles and Snow's strategic types: A comprehensive assessment of reliability and validity. *Acad. Management J.* **33**(4) 817–832.

Walker, O. C., Jr., H. W. Boyd, Jr., J. Mullins, J. C. Larréché. 2003. *Marketing Strategy: Planning and Implementation,* 4th ed. Irwin/McGraw-Hill, Homewood, IL.

Wedel, Michel, Wagner A. Kamakura. 2000. *Market Segmentation: Conceptual and Methodological Foundations,* 2nd ed. Kluwer, Boston, MA.

Wernerfelt, Berger. 1984. A resource-based view of the firm. *Strategic Management J.* **5** 171–180.